
Precision Dairy Monitoring Opportunities and Challenges
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Precision Dairy
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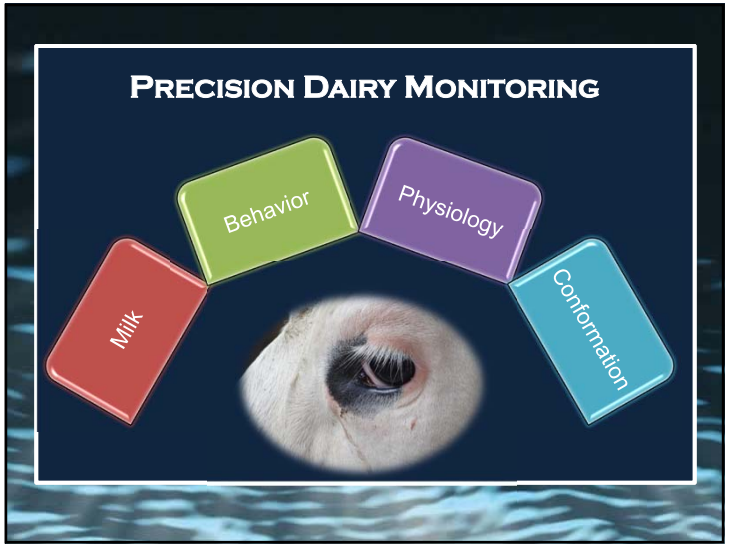
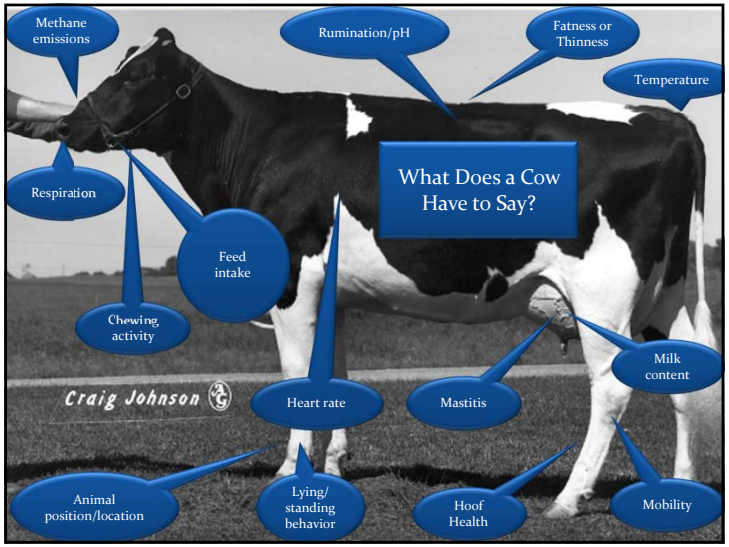
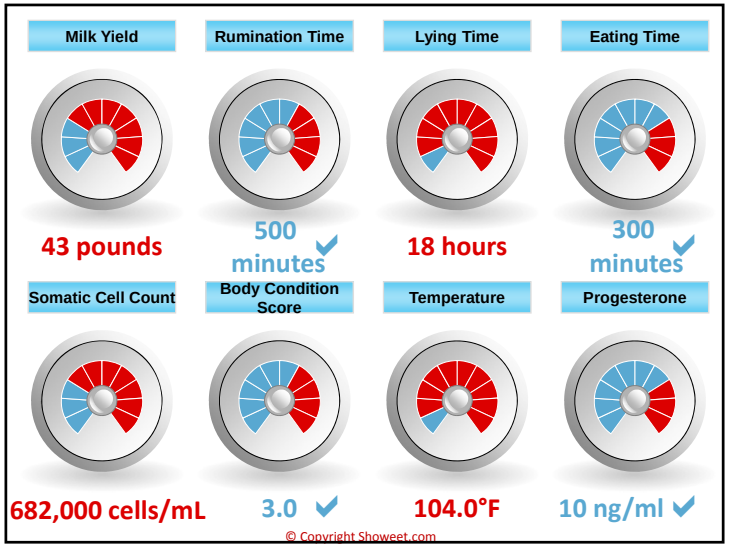

Precision Dairy Monitoring
Behavior
Physiology
Milk
Conformation


Methane emissions
Rumination/pH
Fatness or Thinness
Temperature
What Does a Cow Have to Say?
Respiration
Feed intake
Chewing activity
Craig Johnson
Heart rate
Mastitis
Milk content
Animal position/location
Lying/ standing behavior
Hoof Health
Mobility


Milk Yield
43 pounds
Rumination Time
500 minutes
Lying Time
18 hours
Eating Time
300 minutes
Somatic Cell Count
682,000 cells/mL
Body Condition Score
3.0
Temperature
104.0°F
Progesterone
10 ng/ml
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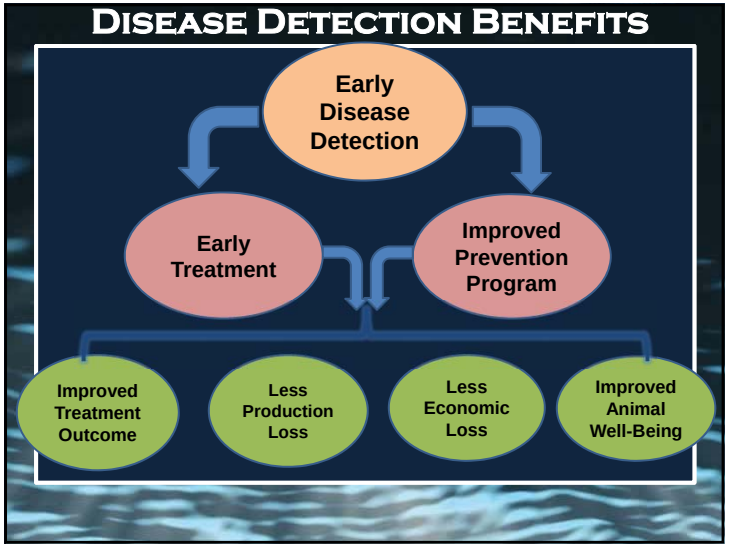
Precision Dairy Monitoring Applications

- Estrus Detection
- Mastitis Detection
- Fresh Cow Disease Detection
- Lameness Detection
- Calving Detection
- Genetic Traits
- Management Monitoring

Precision Dairy Benefits

- Improved animal health and well-being
- Early detection
- Increased efficiency
- Improved product quality
- Minimized adverse environmental impacts
- More objective measures

Disease Detection Benefits

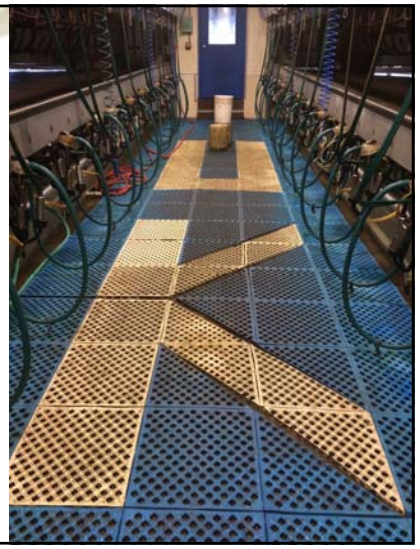


The Options Are Endless

Ideal Technology

- Explains an underlying biological process
- Can be translated to a meaningful action
- Cost-effective
- Flexible, robust, reliable
- Simple and solution focused
- Readily available information

Parlor Precision



Inline Somatic Cell Count

Mastiline

Lely MQCC

DeLaval OCC

CellSense

Spectroscopy

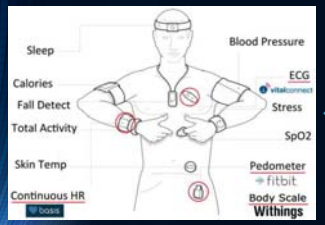
- Visible, near-infrared, mid-infrared, or radio frequency
- Indirect identification through changes in milk composition
- AfiLab uses near infrared
  - Fat, protein, lactose

DeLaval Herd Navigator™

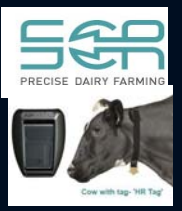
Milk measurements

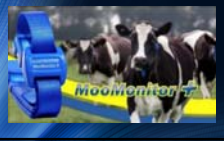
- Progesterone
  - Heat detection
  - Pregnancy detection
- LDH enzyme
  - Early mastitis detection
- BHBA
  - Indicator of subclinical ketosis
- Urea
  - Protein status

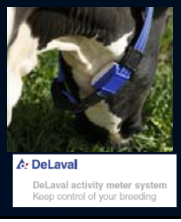
Wearable Technologies



Neck or Ear Based Behavior Monitoring







Physiology Monitoring

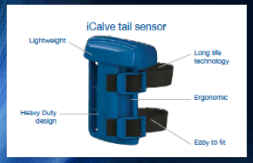
Lying Behavior Monitoring

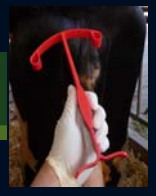
On-farm evaluation of lying time:

- Identification of cows requiring attention (lameness, illness, estrus)
- Assessment of facility functionality/cow comfort
- Assess animal well-being

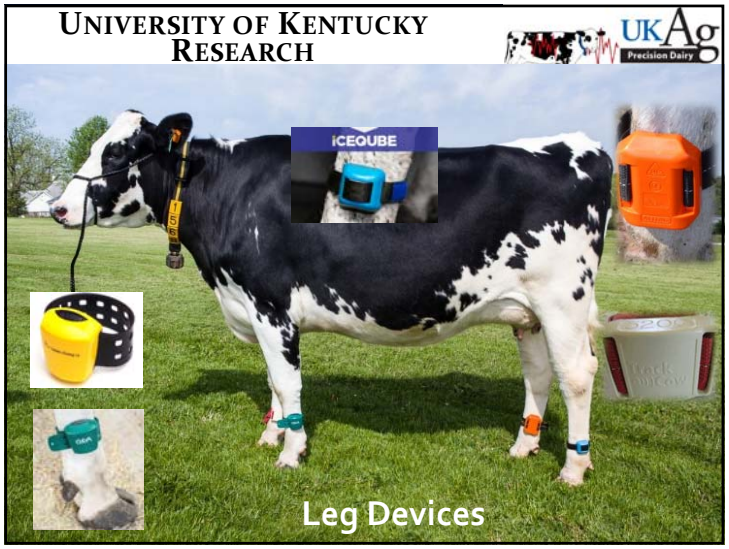
Real Time Location Systems

Calving Detection





University of Kentucky Research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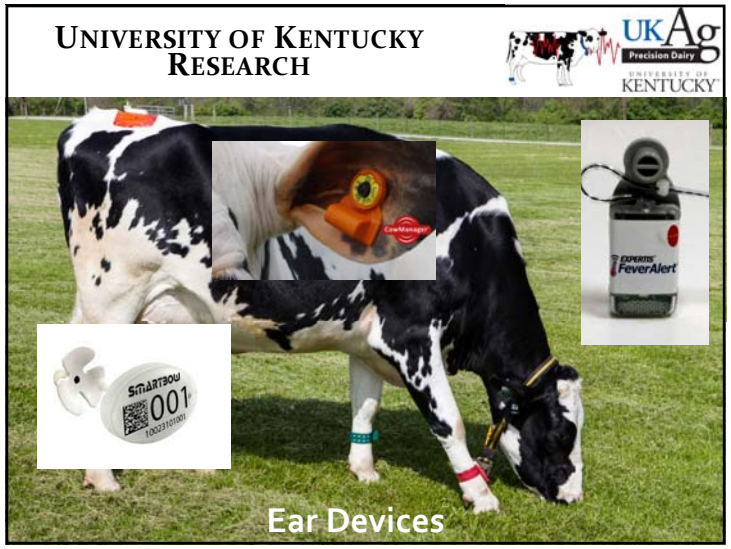
UKAg Precision Dairy
iCEQUBE
Leg Devices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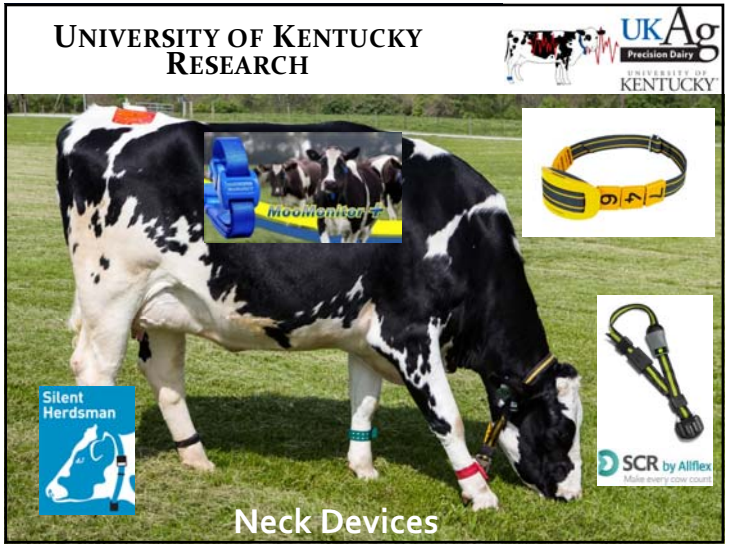
UKAg Precision Dairy
UNIVERSITY OF KENTUCKY
SMARTBOW
001
FeverAlert
Ear Devices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UKAg Precision Dairy
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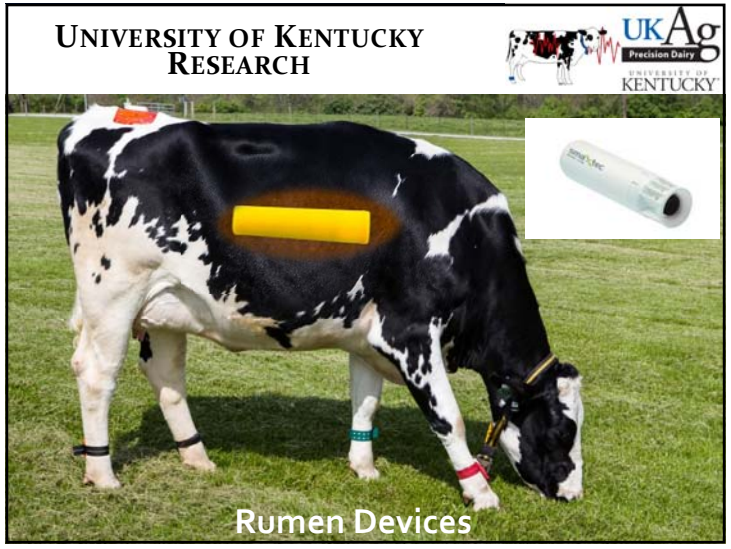
Silent Herdsman
SCR by Allflex
Neck Devices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Rumen Devices

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Calving Devices

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Parlor Devices

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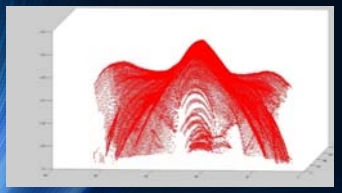
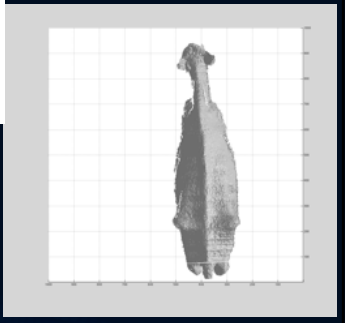
New Technology Development

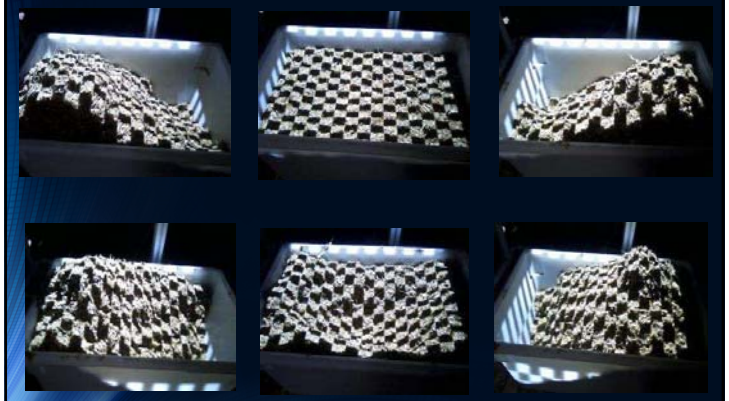
3D BCS Automation





Lau, Shelley, Stone, and Bewley, 2014

Feed Intake: 3D Imaging (99% R^2)



Shelley et al., 2013

Sleep Monitoring System

- Sleep importance-immune function, well- being, disease, facilities decisions
- Develop and test a non-invasive monitor using an accelerometer
- Measure head and neck movement to classify sleep/wake behaviors through human observation
- 92 to 93% agreement with human observations

Klefot et al., 2013

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Lying, Rumination, and Feeding Validation

- Technologies :
  - AfiAct Pedometer Plus
  - Cowalert IceQube
  - CowManager Sensoor
  - Smartbow
  - Track a))) Cow

Borchers et al., 2015

Lying Behavior

Technology	Number of cows	Correlation to visual observations (r)[1]
CowAlert IceQube	48	1.00**
Track a Cow	44	1.00**
AfiAct Pedometer Plus[2]	48	1.00**

[1]Correlation coefficients were performed accounting for repeated measures, or directly across all observations.
[2]Data collected using a handheld reader for the Afi Pedometer Plus system. Data was collected once approximately every 15 minutes.
*-Denotes significance at *P < 0.05, **P < 0.01.

Borchers et al., 2015

Feeding Behavior

Technology	Number of cows	Correlation to visual observations (r)[1]
CowManager SensOor	46	0.87**
Track a Cow	41	0.93**

[1]Correlation coefficients were performed accounting for repeated measures, or directly across all observations.
*-Denotes significance at *P < 0.05, **P < 0.01.

Borchers et al., 2015

Rumination Time

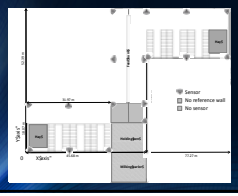
Technology	Number of cows	Correlation to visual observations (r)[1]
CowManager SensOor	46	0.69**
Smartbow	46	0.96**

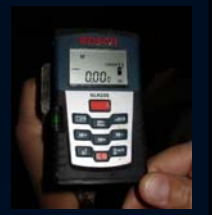
[1]Correlation coefficients were performed accounting for repeated measures, or directly across all observations.
*-Denotes significance at *P < 0.05, **P < 0.01.

Borchers et al., 2015

Smartbow Position Monitoring

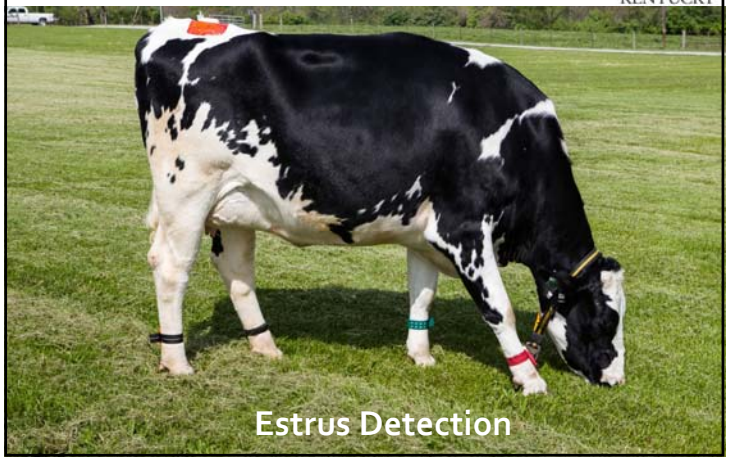
- Eartag based system-triangulation
- Comparison with laser measure device
- Root mean square error of (x,y)
- 1.22 m (SE 1.32 m)
- Close estimate of the location of the cow





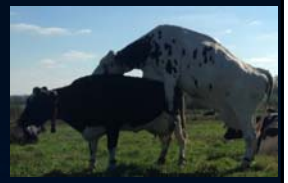
Wolfger et al., 2014

University of Kentucky Research



Multiple Technology Efficacy

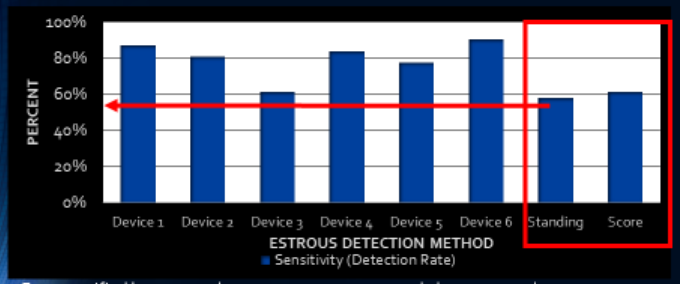
- 109 lactating Holstein cows at the University of Kentucky Coldstream Dairy
- Modified G7G-Ovsynch used for synchronization at 45-85 DIM
- Estrus gold standard was verification of luteal regression and ovulation using temporal progesterone patterns and ultrasonography
- Visual observation 4X a day for 30min each for 4 days
- All cows equipped with 9 commercially available precision dairy technologies



Mayo et al., 2015

Efficacy of alerts generated by precision dairy technologies

Efficacy[1] of alerts generated by automated estrus detection devices (n=35)



[1]Estrus verified by temporal progesterone patterns and ultrasonography

All precision dairy technologies tested were similar in sensitivity and accuracy of alerts generated for estrus

All precision dairy technologies tested were better than visual observation

Mayo et al., 2015

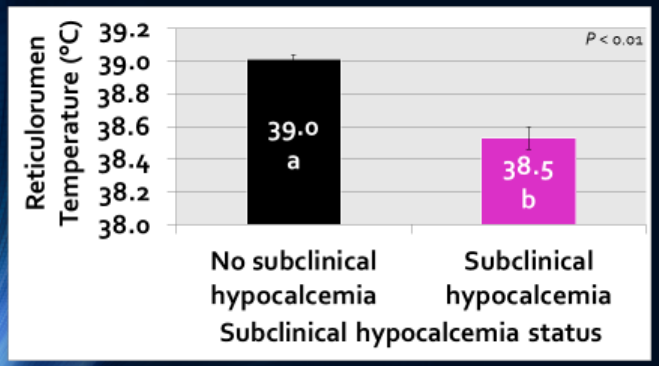
University of Kentucky Research

Changes Around Mastitis

Variable	N	Mean difference	Standard Error	P-value
Rumination time (min/d)	44	-109.10	13.03	< 0.01
Neck activity	44	-81.18	11.53	< 0.01
Milk yield (kg)	57	-5.10	0.72	< 0.01
Reticulorumen temperature (° C)	45	0.47	0.07	< 0.01

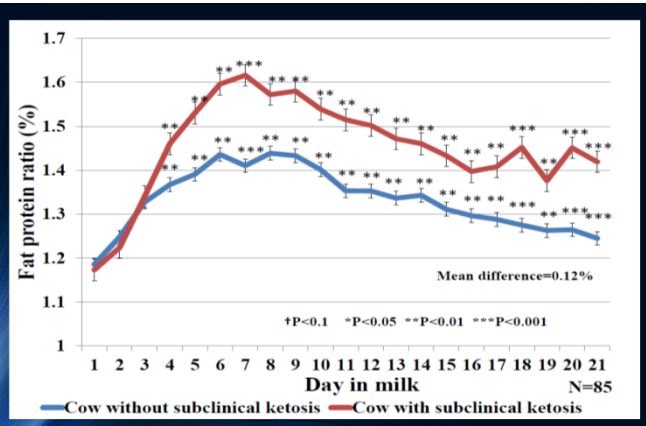
Stone et al., 2013

Reticulorumen temperature by subclinical hypocalcemia status



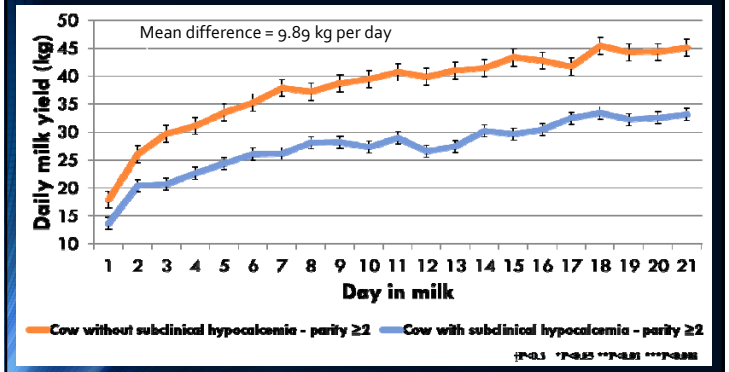
Stone et al., 2013

AfiLab Fat:protein ratio for cows with and without subclinical ketosis



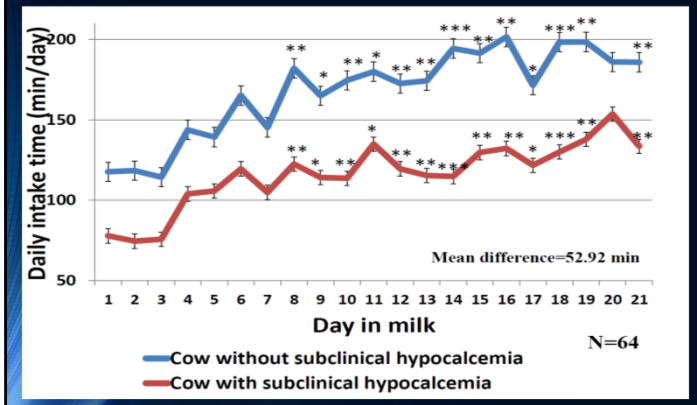
Tsai et al., 2015

Afi milk yield for cows with and without subclinical hypocalcemia



Tsai et al., 2015

Track)) a cow feedbunk time for cows with and without subclinical hypocalcemia



Tsai et al., 2015

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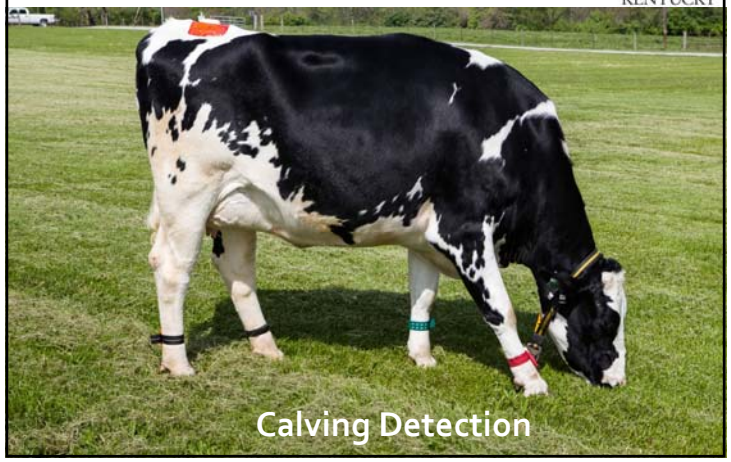
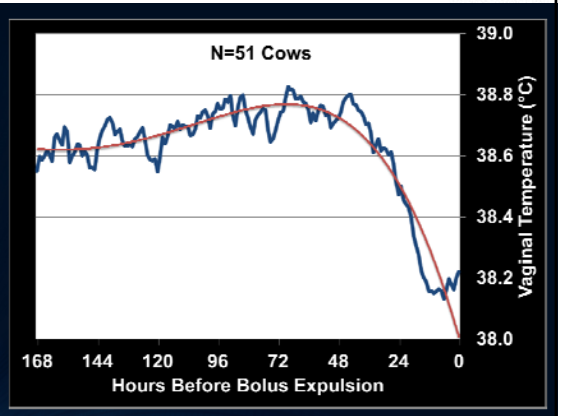
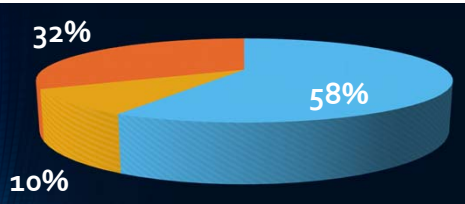


Change in Vaginal Temperature Before Calving



Hardy et al., 2015

Calving Alerts



- Alert Within 48 Hours Before Bolus Expulsion
- No Alert Provided
- Alert Greater than 48 Hours Before Bolus Expulsion

n = 62

Hardy et al., 2015

Calving Detection with Neural Network

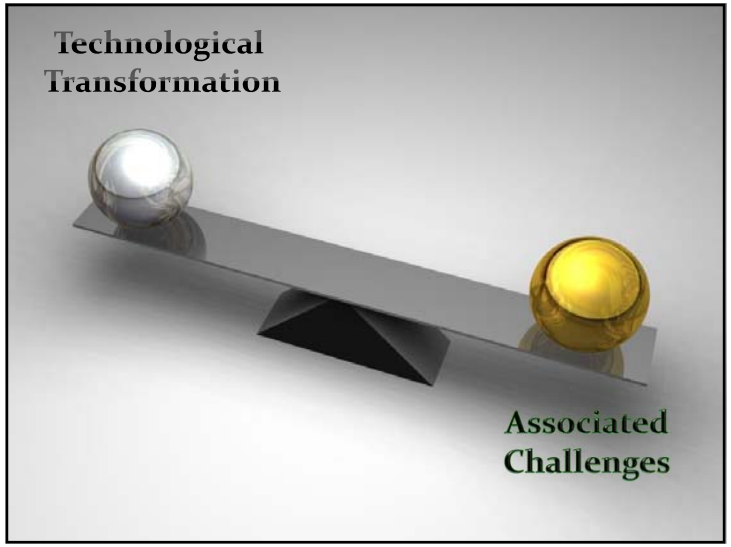
Technology	Sensitivity	Specificity
HR Tag	55.6%	91.8%
IceQube	88.9%	93.5%
Combination	100.0%	96.5%

Borchers et al., 2014

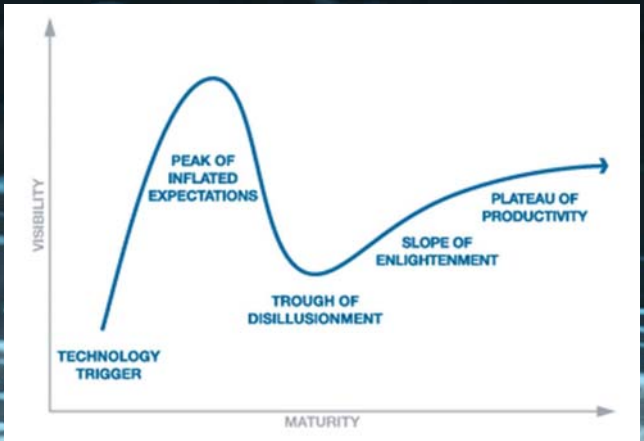
University of Kentucky Research

Group or Cow Level Data

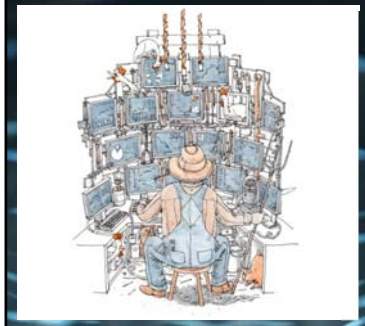
- Most useful for within group or within herd changes
- May be useful for cohort comparisons
- Keep in mind natural variation and lag
- Be extremely cautious comparing across herds
- Question conventional wisdom



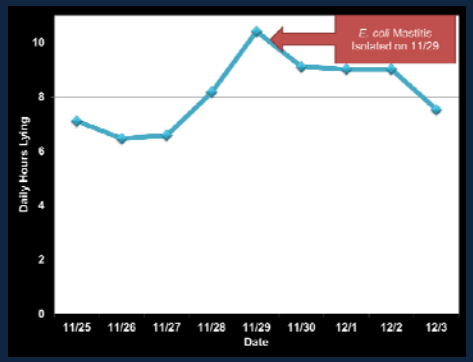
Gartner Product Life Cycle



UK Dairy Office



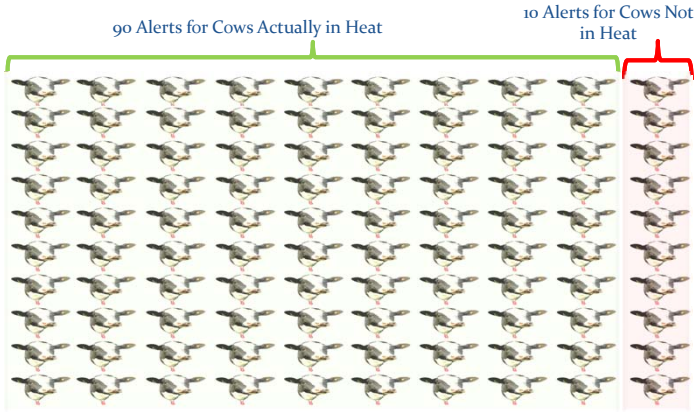
Graph Marketing Approach



How Many Cows With Condition Do We Find?

Example: 100 estrus events

How Many Alerts Coincide with an Actual Event?



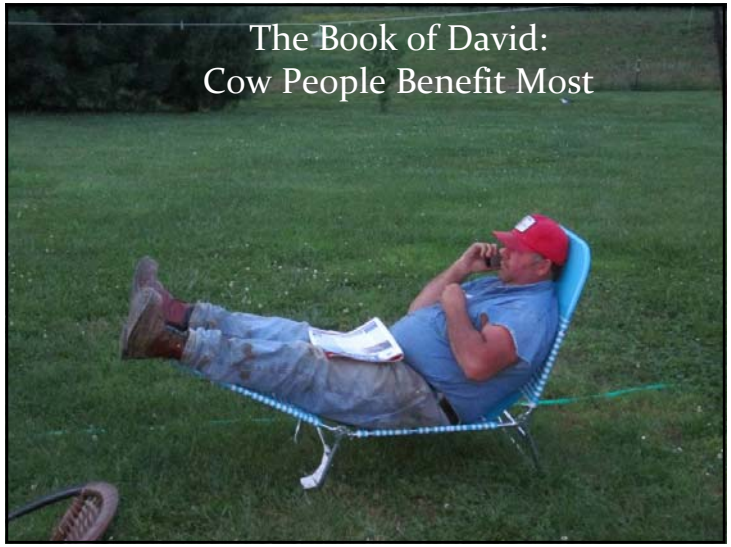
Example: 100 estrus alerts

Timeline Alert/Event Comparisons

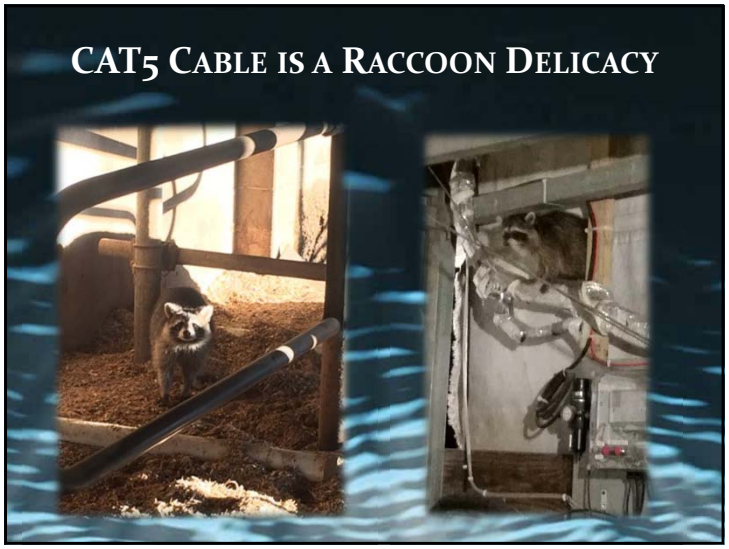
Eckelkamp et al., 2016

Handling Data

- Protocols for Handling Alerts
- Natural Reactions of Healthy Cows
- Repeat Alerts
- Failed Devices
- Backup Plan for System Outage
- Data Security/Ownership



CAT5 Cable is a Raccoon Delicacy



WARNING:
Lightning will strike the same technology twice

Questions Producers Should Ask

1. What are the sensitivity/specificity for condition of interest?
2. What percent of devices fail per year?
3. What is the warranty policy?
4. What is the policy for upgrading to new versions of devices?
5. What are full costs (hardware, devices, maintenance, data storage)?
6. What protocols are available for handling alerts?

What's Next?

- More sensor systems
  - Milk and image based
- Machine learning (i.e. neural networks, fuzzy logic)
- Individual farm algorithms
- Cloud-based data integration
- User groups
- Increased farmer demand for quality alerts

Moving Forward

Questions?

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